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Prediction of future climate in Ngerengere river catchment, Tanzania

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ABSTRACT

Prediction of future climate forms one of the tenets of assessing impacts of climate change in various aspects of livelihoods. The ability to validate climate variables generated by relatively coarse global models, at the desired scales, not only adds value to the usefulness of such models but also engenders research on impacts of climate change in various domains. In this study, one of the protocols for downscaling climate variables from coarse Global Circulation Models (GCM), the Long Ashton Research Station Weather Generator (LARS-WG) was applied in the Ngerengere catchment in Tanzania. LARS-WG is a stochastic weather generator which can be used for generation of weather data at single site under both current and future climate condition.

The LARS-WG model was calibrated and validated using the observed daily rainfall data for the period 1971–2000 (30 years) in Ngerengere catchment. LARS-WG calibration results indicate a good fit between observed and generated average daily rainfall and temperature indices. The calibrated model was then used to downscale climate attributes from GCMs with appreciable results where it was observed that LARS-WG performed well in generating future rainfall and temperature data series. The results indicated an increase in minimum and maximum temperature between 0.2 and 2.6 °C in the 2050s and between 2.7 and 4.4 °C in the 2080s. The lowest increase in future temperature was noted to occur in October and November and the highest increase to occur in May, June and July. Future rainfall was predicted to decrease by 12–37% in April, May, June and July, while rainfall in the remaining months, was predicted to increase by 3–58%.

1. Introduction

Climate change is considered to be the biggest threat of the 21st century and sustainable development in the entire world (IPCC, 2014; Lema and Majule, 2009). Climate change has been confirmed to be impacting almost all parts of the world but the African continent is considered to be the most vulnerable region to shocks of climate change and climate variability due to numerous stresses and low adaptive capacity (IPCC, 2014). Despite various adaptation measures to current climate change impacts, such interventions have been considered insufficient for future changes in climate (IPCC, 2014).

Among some of the threats posed by climate change include change in global average/mean surface temperature which is forecasted to increase by 1.1 °C–6.4 °C for the upcoming century. Such an increase in temperature can lead to unprecedented change and shifts hydrological cycle with impacts on precipitation and evapotranspiration. (Middelkoop et al., 2001). Future predictions of climate variables by the Intergovernmental Panel on Climate Change (IPCC, 2014) revealed an increase in the global temperature values of 0.2 °C (when low emission scenario is considered in predictions) to over 5 °C per decade (for high emission scenario). According to IPCC (2014), future precipitation is predicted to be more variable. Precipitation is also predicted to increase by between 5% and 20% for November, December, January and February. Nevertheless, a decrease of 5–10% is predicted to occur for the remaining months (IPCC, 2014). Several studies including Lubini and Adamowski (2013) have highlighted that, temperature in many parts of Africa will increase by 0.7 °C, with 0.05 °C increase in mean temperature values per decade in the 20th century. However, annual precipitation in East Africa countries is predicted to have a variable trend (increase or decrease). Many climate change studies in East Africa suggest an increased temperature and precipitation during this century (Mango et al., 2011). However, changes in annual precipitation are predicted to be in the range of 3% decrease to 25% increase, with a substantial seasonal variability.

According to Tanzania National Report on Action Plan for Climate Change 2015,the mean annual temperature in Tanzania is forecasted to increase between 1 °C and 2.7 °C during the 2060s and up to 4 °C in the 2075s with central parts of the country forecasted to experience higher temperature rise than the coastal areas (Shemsanga et al., 2010). Unlike temperature, rainfall trend in Tanzania is forecasted to be more varying

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with unstable intensities (IPCC, 2014). The country is forecasted to have up to 20% decrease in mean annual rainfall for the central regions of the country, while the same is forecasted to increase between 20% and 50% in other parts of the country (northern, southern and around Lake Victoria basin) (Mwandosya et al., 1998). Despite these unprecedented changes at national level, it is crucial to establish and validate climate change scenarios and output from GCM's at local scales (Rajan, 2014). The GCMs offer an extensive view of atmospheric variability at coarser scales. However, the usefulness of such coarse climate signatures is restricted to large spatial resolutions mostly exceeding fifty thousand square kilometers (50,000 km^2) (Wilby and Harris, 2006) and thus making them unsuitable for interpolation at small scales. Downscaling of climate variables generated by GCMs to finer and more useful resolution is therefore crucial to address the divergence in the resolutions of what GCMs can deliver and what climate change impact assessors need (Mullan et al., 2012). Downscaling is a way for creating locally related climate data from GCMs outputs. The main aim of downscaling process is to link the global scale forecasts with the regional forecasts for generation of regional detailed local or site-specific data (Cherie, 2013). Downscaling is intended to bridge the gap between information provided by course resolution (GCM) and the higher resolution local scale data needed for impact assessment at local scale (Mkhandi et al., 2010; Dessu and Melesse, 2012).

Such an approach was applied in the Ngerengere river catchment (Fig. 1) which is one of the sub-catchment of the Wami/Ruvu sub-basin in Tanzania. The catchment serves as the source of water supply for the urban areas of Morogoro Municipality as it drains its water into the Mindu Dam. The catchment is currently experiencing an increase in water shortage due to increasing demand of water use as well as associated impacts of climate change among other factors. Such challenges have continued to affect the socio-economic activities in the catchment and has intensified water related conflicts in the catchment (Hubert et al., 2006).

2. Study area description

2.1. Location

Ngerengere River catchment, Fig. 1, is located in the middle of Wami-Ruvu sub-basin between latitude 6° 30′ 00″ and 7° 10′ 00″ South and between longitude 37° 58′ 26″ and 38° 31′ 30″ East and has an area of approximately 2780 square kilometers. The Ngerengere river originates from the Ulugulu mountains and covers a huge percentage of Morogoro region such as the Morogoro urban district and some parts of the Morogoro rural districts. The catchment consists of one dam (Mindu dam) which is the main fresh water source for Morogoro urban areas and other socio economical activities such as agriculture and fishing among others. The river finally joins the lower Ruvu River which discharges its water into Indian Ocean as indicated in Fig. 1.

2.2. Climate

The catchment receives bimodal rainfall. The first short rainfall season (*Vuli*) starts in November to January followed by short dry season in February. The long rain season (*Masika*) starts in March ending in May then followed by a long dry season between June to

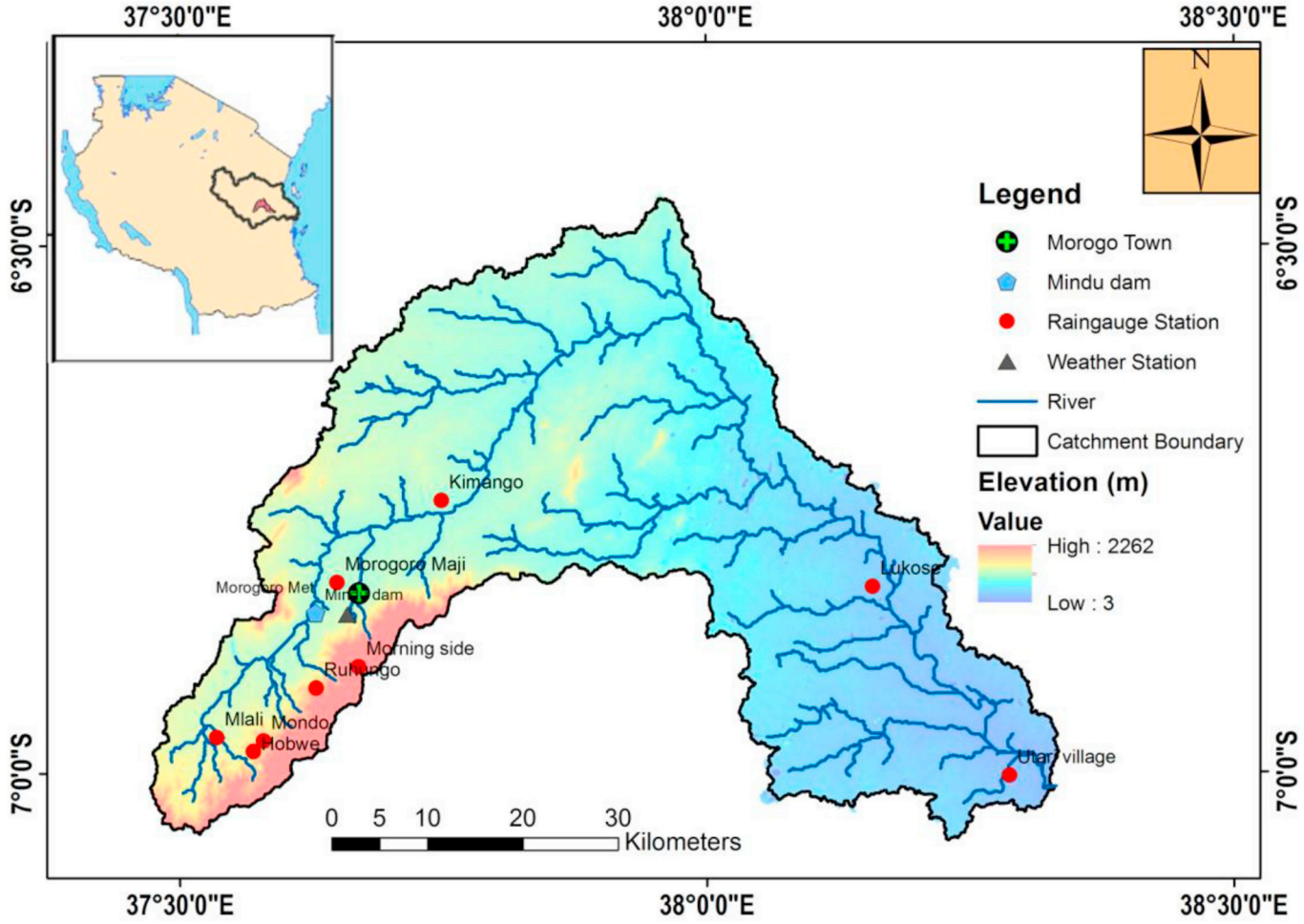

Fig. 1. Location of the Ngerengere catchment.

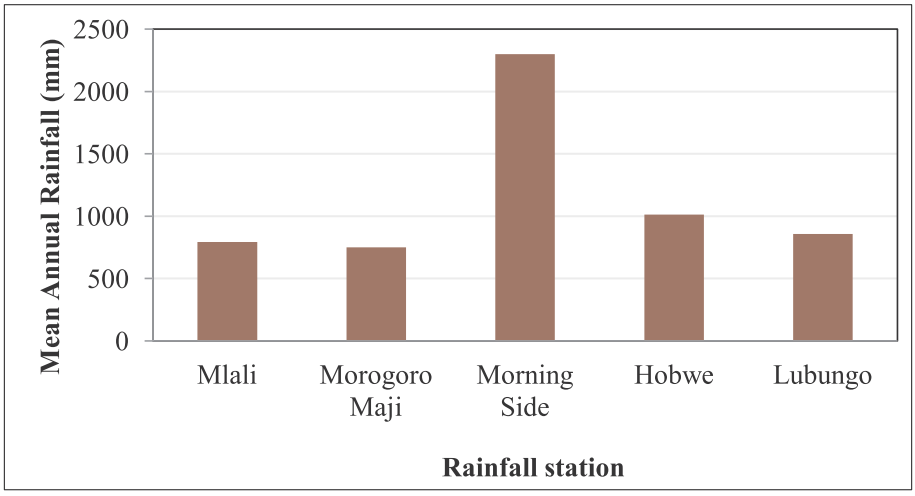

Fig. 2. Mean Annual rainfall of the study area.

October. The mean annual rainfall for most parts of the catchment varies between 800 mm and 1000 mm, as indicated in Fig. 2, but increases to more than 2000 mm in the Uluguru Mountains on the upstream of the catchment. A similar observation was noted by Natkhin et al. (2013). The location of raingauge stations in the catchment is as shown in Fig. 1.

Additionally, Ngerengere catchment has nearly uniform mean monthly temperature. The coldest month is August (18 °C) and the hottest month is February (32 °C). The catchment annual average temperature is about 26 °C, while annual potential evaporation is estimated to be ranging between 1500 and 1700 mm in the catchment of which seems to be higher than the annual rainfall (Natkhin *et.al.,* 2013).

3. Material and methods

3.1. Meteorological data acquisition

Daily values of rainfall data were obtained from Tanzania Meteorological agency (TMA) for Morogoro station, which is the only meteorological station located within the catchment. Rainfall data for other rain stations located within the catchment with data spanning-over 30 years were collected from Wami-Ruvu River Basin Office (WRBWO). The data from these stations were used for generation of future climate data (precipitation, and maximum and minimum temperature). Thirty years of daily precipitation and temperature records representing the baseline climate (1971–2000) were chosen for calibration of the downscaling exercise. The metadata of these stations is as indicated in Table 1 while Fig. 3 shows the span and availability of data in each station.

Minimum and maximum temperature obtained from Morogoro Meteorological station, which is the only station that measures temperature within the catchment, was used for the downscaling exercise.

Table 1
Rainfall stations.

Station ID	Station Name	Latitude (°)	Longitude (°)	Elevation (m)
9637046	Morning side farm	−6.90	37.67	1371
9637047	Hobwe	−6.98	37.57	742
9637048	Luhungo	−6.92	37.63	880
9637049	KwaNdewa-Masa	−6.97	37.58	882
9637051	Mlali	−6.97	37.33	594
9637052	Morogoro Hydromet	−6.82	37.65	512
9637076	Morogoro Met station	−6.85	37.66	526

3.2. Time series analysis

The objective of undertaking time series analysis for this study was to check for stationarity and detect outliers in time series data. Time series analysis performed in this study included (i) change point analysis and (ii) sliding correlation analysis.

3.2.1. Change-point analysis

Change point analysis is used as one of the method to check the stationarity of a time series data. There are a range of statistical tests for checking for shifts in meteorological time series, also highlighted in Guerreiro et al. (2014) and detailed reviewed in Kundzewicz and Robson (2004). This study employed a widely used Pettitt (1979) test to check for the presence and the exact timing of an abrupt change in the rainfall data. This method was selected because it is a rank-based method, non-parametric, distribution-free and can take into account outliers. Annual mean values of rainfall from the selected six rainfall stations within the catchment were first estimated. Moreover, since it is known that there is no single acceptable and most reliable method of change point detection, it is a common norm to use a number of methods to check if they give similar results (Vu et al., 2018). Likewise in this study, a combination of a number of tests i.e. the Pettitt test, Buishand test, Lee and Heghinian test and the segmentation method of Hubert were used to detect if there was a change in the observed time series. To perform these analysis, the Khrono-Stat 1.01 software was used. The software was developed by the French Institute of Research for Development (IRD) to test for non-stationarity in the time series data. The null hypothesis tested is that there is no break in the time-series input data.

3.2.2. Sliding correlation analysis

The sliding correlation analysis was also performed to detect any outlier in the observed time series data for rainfall data, in order to detect data points that diverges from historical patterns so as to check consistency in the observed data. The procedure involved (i) defining data range for analysis (ii) computing correlation coefficients between the two series for every overlapping successive data set equal to the window size defined above (iii) repeating the above procedure for all the data set in the series.

3.3. Development of climate change scenarios

3.3.1. Statistical downscaling using LARS-WG

This study used Long Ashton Research Station Weather Generator (LARS-WG) to generate future daily rainfall as well as observed

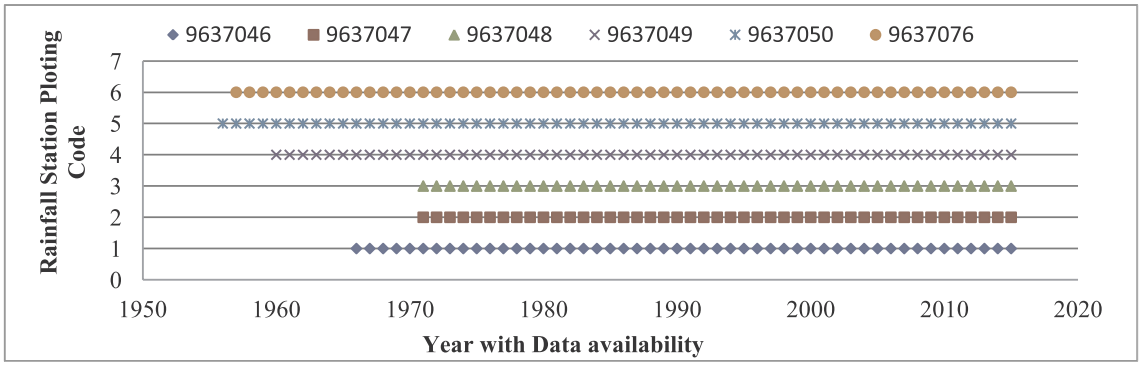

Fig. 3. Span and availability of rainfall data (available data ≥25% per year).

maximum and minimum temperatures of which is needed for generation of future streamflow. LARS-WG is a stochastic weather generator which can be used for generation of weather data at single site under both current and future climate condition (Semenov and Barrow, 2002). It employs a semi-empirical distribution (SED) and the cumulative probability distribution function (PDF) with 23 intervals, to estimate probability distributions of dry and wet day series, daily precipitation, temperature and solar radiation (Sarkar et al., 2015).

LARS-WG version 5.0 is able to generate high resolution climate change scenarios over a region using direct outputs from the GCMs (Shrestha et al., 2017; Xu et al., 2012). LARS-WG can generate synthetic daily data of precipitation, minimum and maximum temperature as well as solar radiation (Xu et al., 2012). For this study, solar radiation data were not relevant, therefore, only the methods for generation of synthetic daily precipitation and minimum and maximum temperature are described.

The methods of generating synthetic weather data of precipitation and temperature using LARS-WG involved three major steps; calibration or site analysis, validation or Q-test i.e. comparison of the statistical properties of synthetic data with the observed data as well as generator or generation of future climate data.

3.3.2. LARS-WG calibration and validation

Model calibration in LARS-WG was performed by executing SITE ANALYSIS. The procedure analyzes the observed daily weather data (precipitation, maximum and minimum temperature) to determine their statistical characteristics.

Validation of the LARS-WG model was done by executing the Q-test analysis so as to confirm the performance of the model. Synthetic weather data with the same statistical characteristics as observed data were generated based on the parameter files that were derived during calibration. This procedure helps to validate the ability of the model to generate synthetic data.

LARS WG model outputs were assessed visually (graphically) and statistically as follow:

i) Evaluation of best fit between observed and simulated average rainfall indices (monthly total amounts, maximum daily amounts) for calibration period
ii) Evaluation of best fit between observed and simulated wet and dry spell lengths, which have resulted into better simulation of sequences of wet and dry days as well as number of dry days and rain days

3.3.3. Generation of future climate scenario

After the LARS-WG model had been calibrated and validated, the generation of the synthetic future climate data for the future time period followed. This procedure was performed by creating a scenario file comprising information about changes in future climatic data (precipitation, minimum/maximum temperature) based on baseline weather data (30 years of observed data). Baseline parameters were then adjusted by the changes for the future period. In this study, IPCC Global Climate Model: HadCM3 and SRES A2 development path were used to generate future thirty (30) years predicted weather data for the future periods of 2050s (2040–2069) and 2080s (2070–2099. The following procedure was used:

i) Monthly rainfall and maximum and minimum temperatures were extracted from selected GCMs at a grid location corresponding to the selected climate station in the study area for baseline period (1971–2000) and future periods (2040–2069 and 2070–2099).
ii) Relative changes between future periods and baseline values of rainfall and temperatures were computed as ratios (rainfall) and differences (temperatures) for each month. For rainfall, the ratio was computed between the rainfall difference (future minus baseline) to baseline rainfall and for temperature the differences were computed as (future minus baseline) temperature.
iii) These changes were used to modify scenario file for each future period by adding the ratios of rainfall to 1.00 or temperature differences to 0.00
iv) Individual scenario files were selected and the calibrated LARS WG was then ran to produce daily time series of rainfall, minimum and maximum temperatures for 30 year future periods (2040–2069, and 2070–2099.

4. Results and discussion

4.1. Time series analysis

Time series analysis was carried out for the purpose of checking for stationarity and outliers in the rainfall data series prior to their use for modeling purposes.

4.1.1. Change-point analysis

The Buishand and Pettitt method showed similar results for all stations, that is, there was no change in the mean annual rainfall series for all rainfall stations except for station 9637048 where an increase change was detected in 1983 (i.e. accepted at 99% CI and rejected at 95% CI and 90% CI). The Lee and Heghinian method detected a break point in annual rainfall series for all the tested rainfall stations as tabulated on Table 2 below.

4.1.2. Sliding correlation analysis

The results of the correlation analysis indicated that, there was no variation in the magnitude and the direction of the correlation coefficients for different segments over the rainfall data series.

Table 2
Change point detection for observed annual rainfall.

Test method		Rainfall station gauge				
		Annual Rainfall				
		9637046	9637047	9637048	9637049	9637052
Buishand Test	Test results	Yes	Yes	No	Yes	Yes
	Break date	–	–	1983↑	–	–
Pettitt Test	Test results	Yes	Yes	No	Yes	Yes
	Break date	–	–	1983↑	–	–
Lee and Heghinian Test	Test results	No	No	No	No	No
	Break date	1999↓	1977↑	1997↓	1977↑	1999↓
Hubert's Segmentation Test	Test results	Yes	Yes	No	Yes	Yes
	Break date	–	–	1983↑	_	–

YES = Null hypothesis accepted, the series are "stationary".
NO = Null hypothesis rejected, the series are not "stationary".
"-" = no break detected.

4.2. Development of climate change scenarios

4.2.1. Calibration and validation of LARS-WG model

4.2.1.1. Rainfall. The LARS-WG model was calibrated and validated using the observed daily rainfall data for the period 1971–2000 (30 years). LARS-WG calibration results indicate better fit between observed and simulated average daily rainfall indices. The model simulated well the mean monthly rainfall amounts for all the stations (Fig. 4) but overestimated monthly maximum daily rainfall amounts for some months (Fig. 5). Moreover, statistical tests were performed by using the Kolmogorov-Simirnov (KS) to test the performance of the model on simulation of rainfall distribution. The LARS-WG model

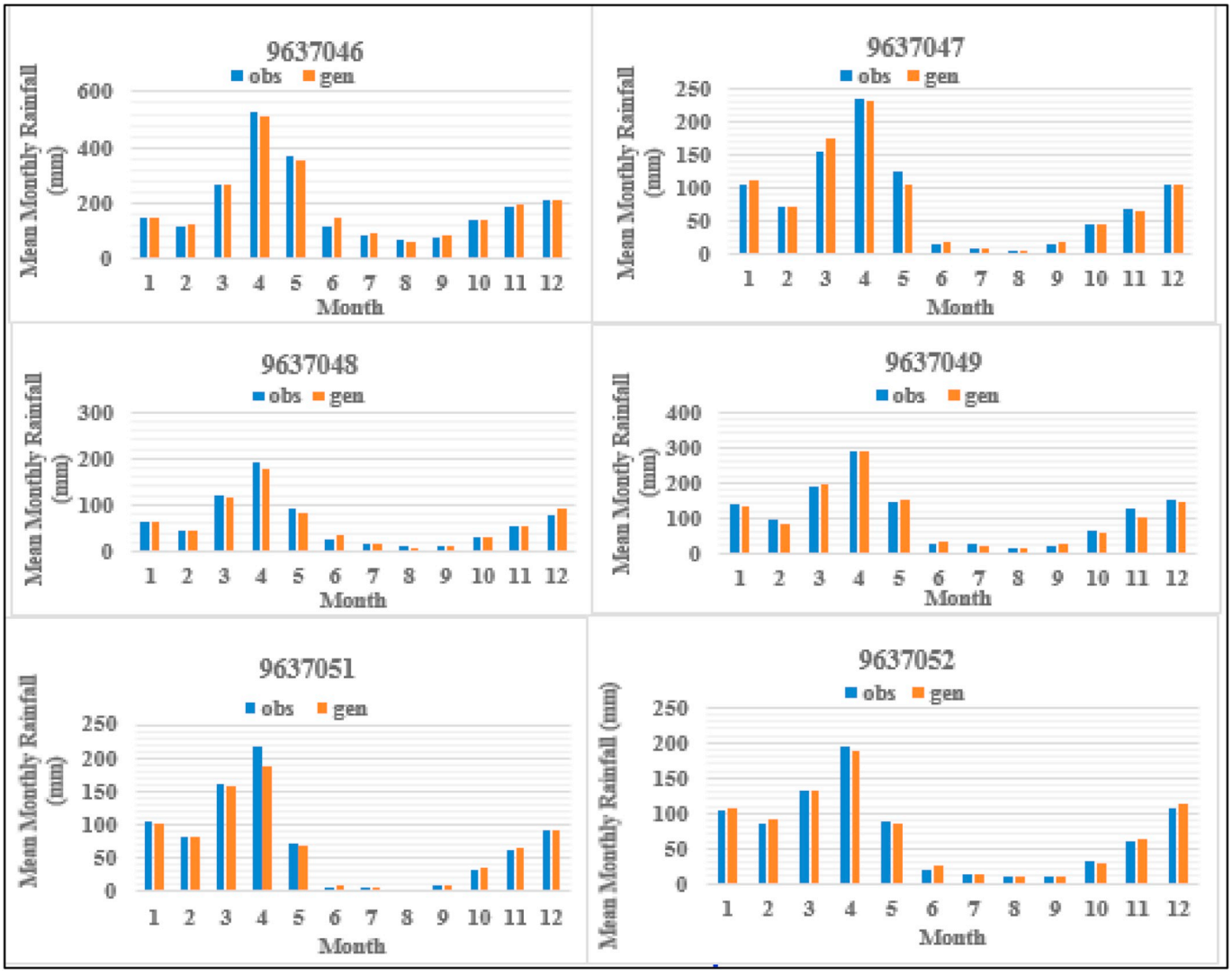

Fig. 4. Calibration of LARS weather generator for mean monthly rainfall amounts at six rain gauge stations in Ngerengere River catchment during 1971–2000.

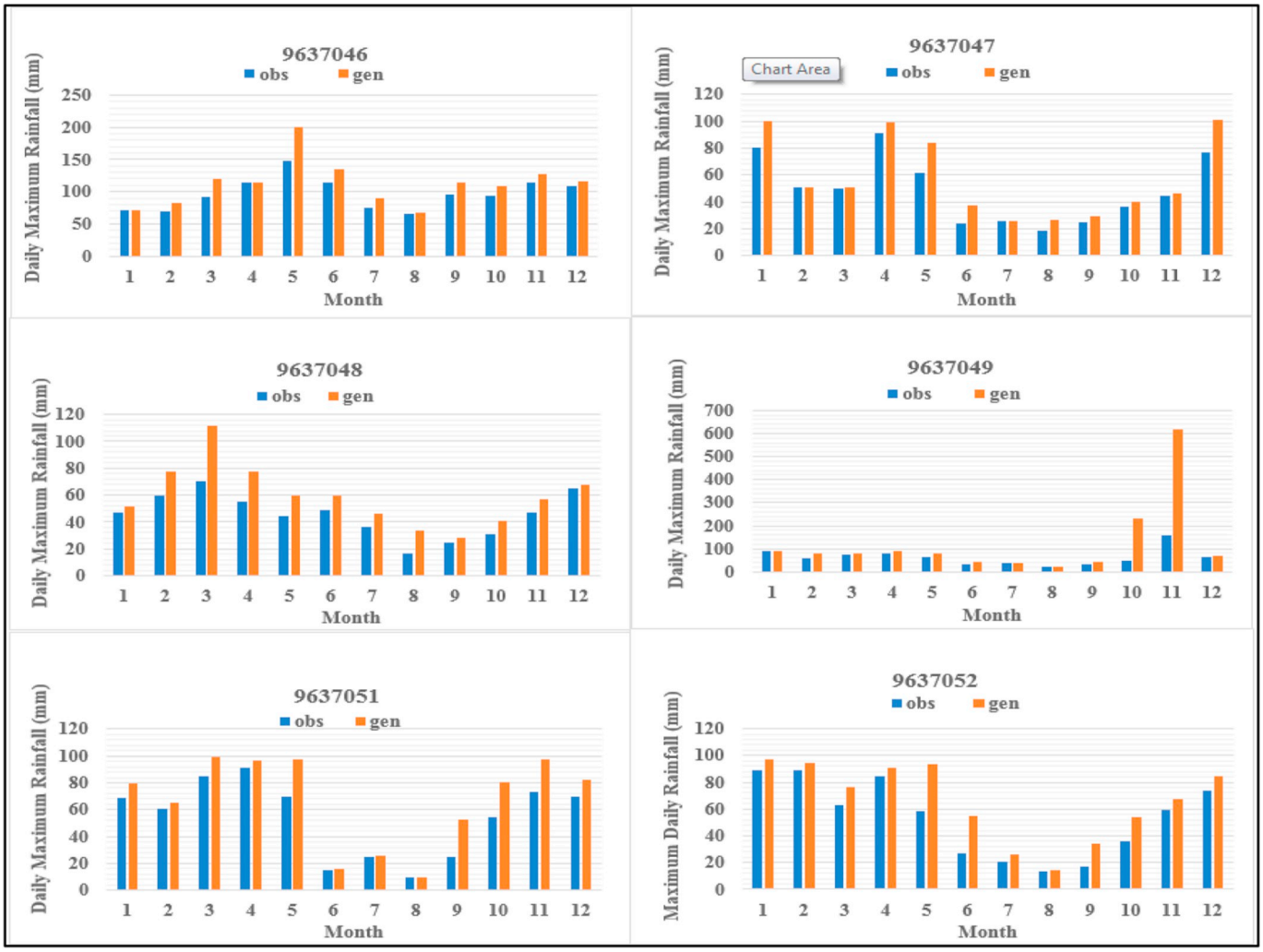

Fig. 5. Calibration of LARS weather generator for daily maximum rainfall amounts at six rain gauge stations in Ngerengere River Catchment during 1971–2000.

Table 3
KS-test for seasonal frost/heat SPELLS distributions.

Season	N	K–S	p-value	Assessment
DJF	12	0.158	0.913	Very good fit
MAM	12	0.113	0.997	Very good fit
JJA	12	0.227	0.537	Good fit
SON	12	0.104	0.999	Very good fit

Table 4
KS-test for daily maximum temperature distributions.

Month	N	K–S	p-value	Assessment
Jan	12	0.105	0.999	Very good fit
Feb	12	0.106	0.999	Very good fit
Mar	12	0.106	0.999	Very good fit
Apr	12	0.053	1.000	Perfect fit
May	12	0.053	1.000	Perfect fit
Jun	12	0.106	0.999	Very good fit
Jul	12	0.106	0.999	Very good fit
Aug	12	0.106	0.999	Very good fit
Sep	12	0.053	1.000	Perfect fit
Oct	12	0.053	1.000	Perfect fit
Nov	12	0.053	1.000	Perfect fit
Dec	12	0.106	0.999	Very good fit

generated well the wet and dry spell lengths both for daily (Table 4) and seasonal rainfall distribution (Table 4). Based on these appreciable results, it was concluded that LARS-WG was capable of generating daily rainfall in the Ngerengere catchment with capacity to predict daily rainfall for future period.

4.2.1.2. Temperature. The LARS-WG generated mean monthly and daily minimum and maximum temperature values of which were observed to match well with the observed values for all months (Fig. 6 (a)). The statistical tests results fitted well for all months (Table 3). The variability pattern of generated temperature is similar to that of the observed series (Fig. 6 (a))

However, to increase the confidence of LARS-WG in simulating future temperature, more statistical tests were performed on its outputs. The tests were meant to examine likeness in the distribution of daily temperature for both observed data and the LARS-WG generated series. LARS-WG performed well in simulating seasonal distribution of heat spell series, as it fitted well both the DJF,MAM and SON months as indicated in Table 3. The model performed well in mimicking the seasonal distribution of heat spell during the JJA season ((Table 3).

LARS-WG model also performed well in simulating distribution of daily temperature for both minimum and maximum temperature in each month. Fitting of daily distribution in all months was observed to match well (Table 4 and Table 5). From these results, it can be established that the LARS-WG was capable of simulating daily temperature distributions in each month and hence can be used to predict future

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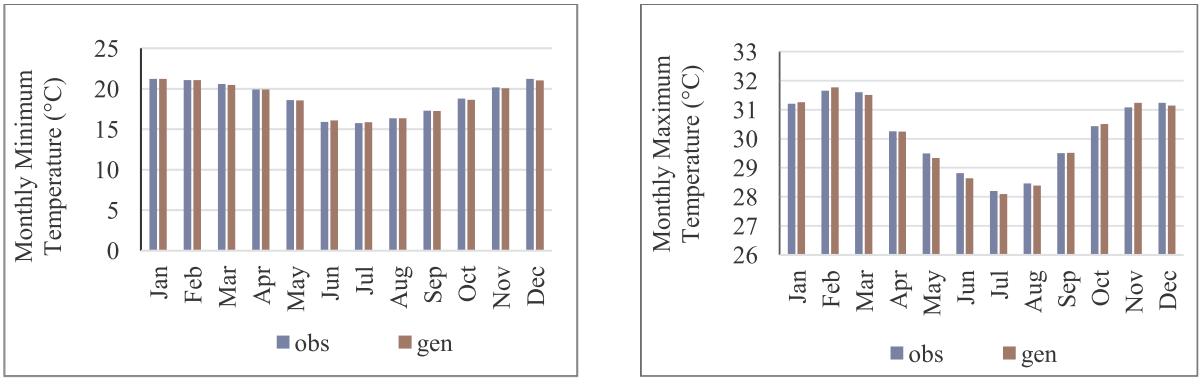
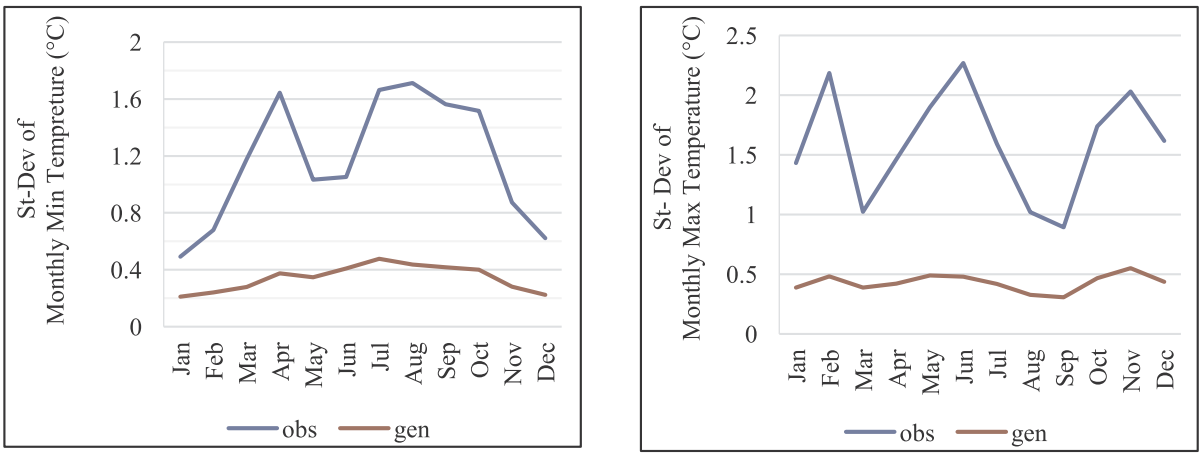


(a)



(b)

Fig. 6. Comparison of (a) monthly mean and (b) standard deviation of observed and LARS generated minimum and maximum temperature (1971–2000).

Table 5
KS-test for daily minimum temperature distributions.

Month	N	K–S	p-value	Assessment
Jan	12	0.053	1.000	Perfect fit
Feb	12	0.053	1.000	Perfect fit
Mar	12	0.106	0.999	Very good fit
Apr	12	0.106	0.999	Very good fit
May	12	0.053	1.000	Perfect fit
Jun	12	0.053	1.000	Perfect fit
Jul	12	0.053	1.000	Perfect fit
Aug	12	0.053	1.000	Perfect fit
Sep	12	0.053	1.000	Perfect fit
Oct	12	0.106	0.999	Very good fit
Nov	12	0.106	0.999	Very good fit
Dec	12	0.158	0.913	Very good fit

daily maximum and minimum temperature for impact analysis. .

4.2.2. Generation of future climate scenarios

The calibrated and validated LARS-WG model for Ngerengere catchment performed well in estimating daily rainfall and daily minimum and maximum temperature. It was therefore applied to predict daily rainfall as well as minimum and maximum temperature for six stations in the study area for future periods of 2040–2069 (2050s) and 2070–2099 (2080s) generated from HadCM3 GCM outputs based on IPCC scenario SRES A2. Analysis of the predicted future daily rainfall, daily minimum and maximum temperature using the LARS-WG model is as presented below.

4.2.2.1. Rainfall. Unlike minimum and maximum temperature, the predicted future rainfall in the catchment did not depict an orderly trend of increase or decrease. The future monthly rainfall amounts are predicted to decrease in the main rainy season (March, April and May) with a decrease in monthly rainfall totals in the months of June, July and August. Future monthly rainfall was noted to have an increasing trend for months just before the the beginning of rainy season i.eSeptember, October and November, as well as in December, January and February. The increase and decrease trends in monhly rainfall was observed in both the near future (2050s) and far future (2080s).. Fig. 7 show that, the highest increase in rainfall amount is predicted to occur in November (57.9%) during the 2050s and in January (51.6%) during the 2080s. A decrease of up to 37.8% and 43.4% was predicted to occur in June during the 2050s and 2080s respectively. Annual rainfall in the study area is predicted to change by −3% to 10.2% in the 2050s and by 0.5%–26.2% during the 2080s (Table 6 and Fig. 8).

4.2.2.2. Temperature. Analysis of downscaled temperature in the catchment showed that, minimum mean monthly temperature are predicted to increase between 0.2 °C and 2.6 °C during the 2050s and between 2.7 °C and 4.7 °C during the 2080s when compared to baseline minimum. temperature. The results also indicated that, maximum mean monthly temperature in the catchment are predicted to increase in the range between 0.3 °C and 2.4 °C and between 2.8 °C and 4.4 °C during the 2050s and the 2080s respectively. The increase in monthly temperature followed almost similar pattern for both minimum and maximum temperature for all future periods as compared to baseline

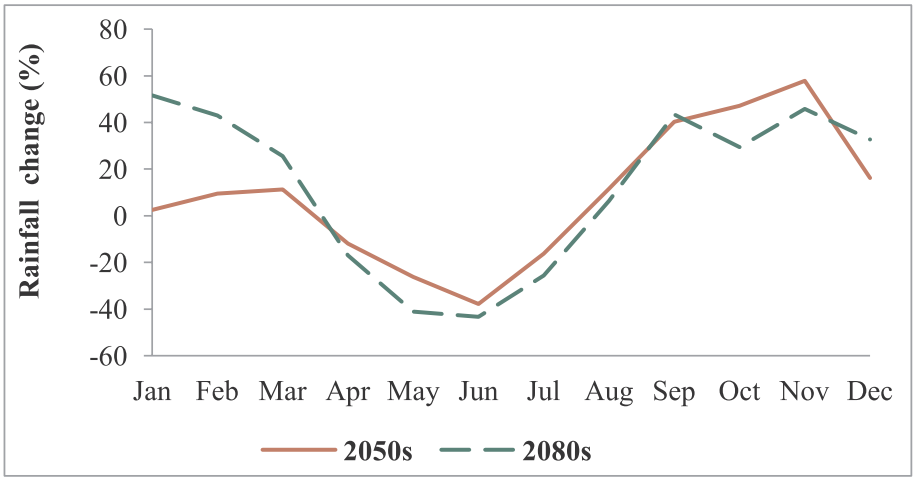


Fig. 7. Projected average rainfall change between baseline and future period (2050s and 2080s) in the Ngerengere catchment.

Table 6
Projected annual rainfall for selected stations in Ngerengere catchment.

Station_ID	Annual Rainfall (mm)			Rainfall change (%)	
	Baseline (1971–2000)	2050s (2040–2069)	2080s (2070–2099)	2050s	2080s
9637052	853	869	940	1.9	10.2
9637049	1361	1500	1462	10.2	7.4
9637048	737	806	930	9.4	26.2
9637047	992	1047	1070	5.5	7.9
9637046	2401	2328	2413	−3.0	0.5

temperature (Fig. 9 (a) and (b)).

The difference in minimum and maximum temperature values for the future periods as compared with baseline period are presented in Table 7 and Table 8 respectively as well as Fig. 9 (a) and (b)). The highest increase in temperature is predicted to occur in May, June and July (around 2.6 °C and 4.7 °C during the 2050s and 2080s respectively) while the lowest increase will be in October and November (around 0.2 °C and 2.7 °C during the 2050s and 2080s respectively).

5. Conclusion

The prediction of future climate in the Ngerengere River catchment was done using the statistical downscaling method (using the LARS-WG). The predictions showed that, minimum and maximum temperature in the catchment are expected to increase in all future periods (2050s and 2080s). The mean monthly minimum temperature in the catchment is projected to increase by 0.2–2.6 °C during the 2050s and between 2.7 °C and 4.7 °C in 2080s. The mean monthly maximum temperature is predicted to increase by 0.3–2.4 °C during the 2050s and between 2.8 °C and 4.4 °C in 2080s. The highest increase in temperature is predicted to occur in May, June and July by a value up to 2.6 °C in 2050s and 4.7 °C in 2080s while the lowest increase is predicted to occur in October and November (0.2 °C in 2050s and 2.7 °C in 2080s). These findings concur with results presented in the IPPC (2007) report and those presented in the draft report on National Action Plan on climate change in Tanzania. In these reports, future temperature prediction for most parts of the African continent has proven to be in an increasing trend. Future values of both minimum and maximum temperature across the continent are expected to increase by 2 °C (when low emission scenario is considered) to up to 5 °C (when high emission scenario is considered) at the end of this century. Since this study used the high emission (SRES A2) it is thereforereasonable that, the results of the predicted future temperature in the catchment obtained from this study is in agreement with finding from other researchers in the region.

Another interesting findings with regards to rainfall predictions in the Ngerengere catchment indicated that, future rainfall does not follow an orderly trend (neither increasing nor decreasing). The changes in mean monthly rainfall amounts are predicted to be highly variable.

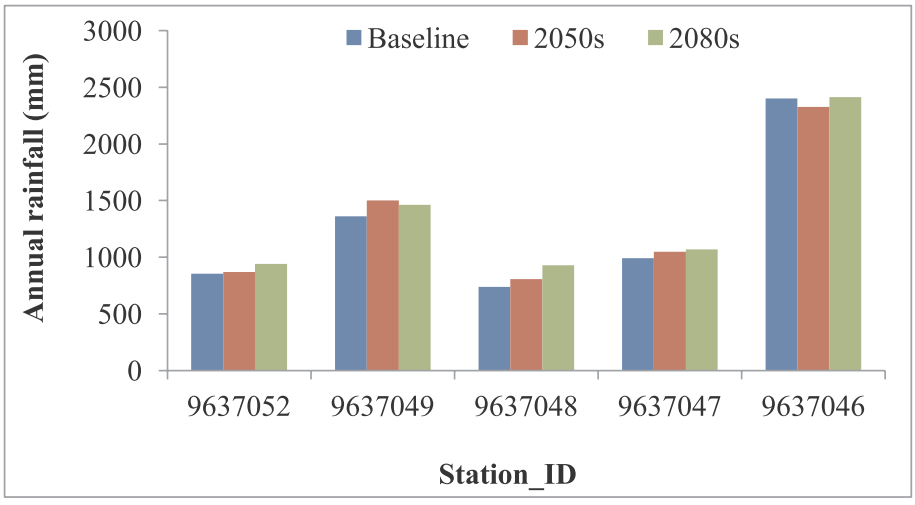


Fig. 8. Comparison of annual rainfall for baseline and future period for selected station in the Ngerengere catchment.

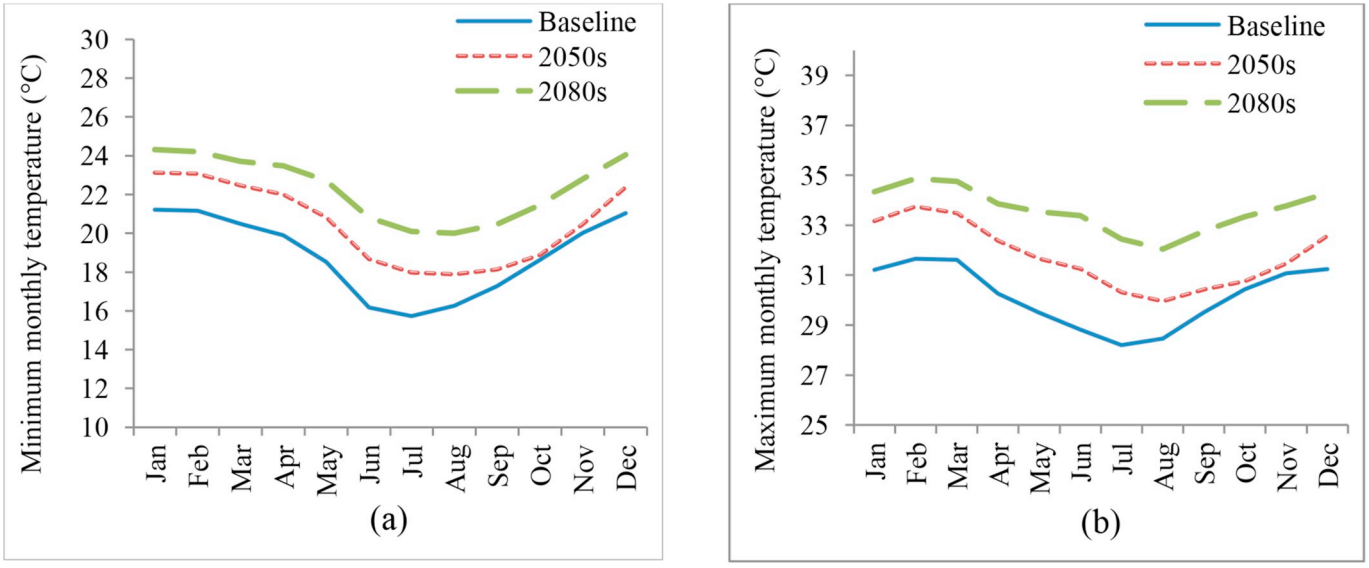


Fig. 9. Comparison of baseline (1971–2000) and future (2050s and 2080s) (a) minimum monthly temperature; and (b) maximum monthly temperature at Morogoro meteorological station.

Table 7
Percentage change in monthly mean minimum temperature calculated by LARS-WG from HadCM3 outputs for A2 emission scenario.

Month	Monthly mean Minimum Temperature (°C)				
	Baseline (2071–2000)	2050s (2040–2069)	Absolute change (2050s)	2080s (2071–2099)	Absolute change (2080s)
Jan	21.22	23.15	1.9	24.32	3.1
Feb	21.17	23.03	1.9	24.26	3.1
Mar	20.49	22.46	2.0	23.69	3.2
Apr	19.89	22.05	2.2	23.6	3.7
May	18.52	20.96	2.4	22.77	4.3
Jun	16.18	18.77	2.6	20.86	4.7
Jul	15.73	17.89	2.2	19.95	4.2
Aug	16.27	17.97	1.7	20.17	3.9
Sep	17.28	18.19	0.9	20.61	3.3
Oct	18.64	18.85	0.2	21.53	2.9
Nov	20.02	20.49	0.5	22.76	2.7
Dec	21.04	22.35	1.3	23.96	2.9

Table 8
Percentage change in monthly mean maximum temperature calculated by LARS-WG from HadCM3 outputs for A2 emission scenario.

Month	Monthly mean Maximum Temperature (°C)				
	Baseline (2071–2000)	2050s (2040–2069)	Δ-change in 2050s	2080s (2071–2099)	Δ-change in 2080s
Jan	31.23	33.31	2.1	34.32	3.1
Feb	31.76	33.86	2.1	34.85	3.1
Mar	31.51	33.52	2.0	34.72	3.2
Apr	30.24	32.4	2.2	33.88	3.6
May	29.35	31.72	2.4	33.71	4.4
Jun	28.87	31.1	2.2	33.19	4.3
Jul	28.09	30.3	2.2	32.49	4.4
Aug	28.42	29.88	1.5	32.03	3.6
Sep	29.55	30.59	1.0	32.91	3.4
Oct	30.55	30.9	0.3	33.42	2.9
Nov	31.05	31.54	0.5	33.89	2.8
Dec	31.26	32.5	1.2	34.41	3.2

Average monthly rainfall amounts in the study area are predicted to decrease in the months of April, May, June and July by 12–38% while rainfall amounts in the remaining months are predicted to increase by 3–58% during the 2050s. Rainfall in the 2080s, for the same months, is predicted to decrease by 16–43% and increase by 6–52% increase respectively. The highest increase in rainfall amount is predicted to occur in November (57.9%) during the 2050s and in January (51.6%) during the 2080s where as a decrease of up to 37.8% and 43.4% was predicted to occur in June during the 2050s and 2080s respectively. The annual rainfall in the catchment is predicted to change by −3% to 10.2% during the 2050s and by 0.5–26.2% in the 2080s. The results of rainfall predictions in this study area within the range of findings by other researchers such as Mwandosya et al., 1998) who predicted change in annual rainfall amounts between −20% (decrease) and 50% (increase) for many parts of Tanzania. Furthermore, IPCC (2014) predicted rainfall trend in tropical countries to be more varying and that their intensities would be unstable. This has proven to be the case for this study as discussed above.

6. Recommendations

Based on the finding discussed herein, there still remains an abundant room for addressing some questions presently unanswered. For further research, the following are some of the suggestions;

i) Since, this study was based on the output of a single global circulation models (HadCM3) and only one emission scenarios (A2), we noted that, there exists other GCMs that can be used to provide climate data for the catchment. Therefore, future studies may consider the other emission scenarios using more than one GCM and compare their results so as to minimize the uncertainties that may be associated with the use of only one GCM.
ii) The GCM outputs for this study were downscaled to catchment level by means of the statistical downscaling method using LARS-WG which is a stochastic weather generator. Other downscaling techniques such as statistical downscaling using SDSM model and weather typing schemes model which are normally useful in climate impact assessments studies could be explored. Therefore, for future studies in the catchment, it is recommended that different downscaling techniques could be applied and comparison of the downscaled variables be made so as to assess and choose the best downscaling tool that can be applied for the Ngerengere catchment.

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